

Some of the slides are copied from the course materials of  
DigiVFX instructed by **Prof. Yung-Yu Chang** at NTU

# Matting

CVFX @ NTHU

30 April 2015

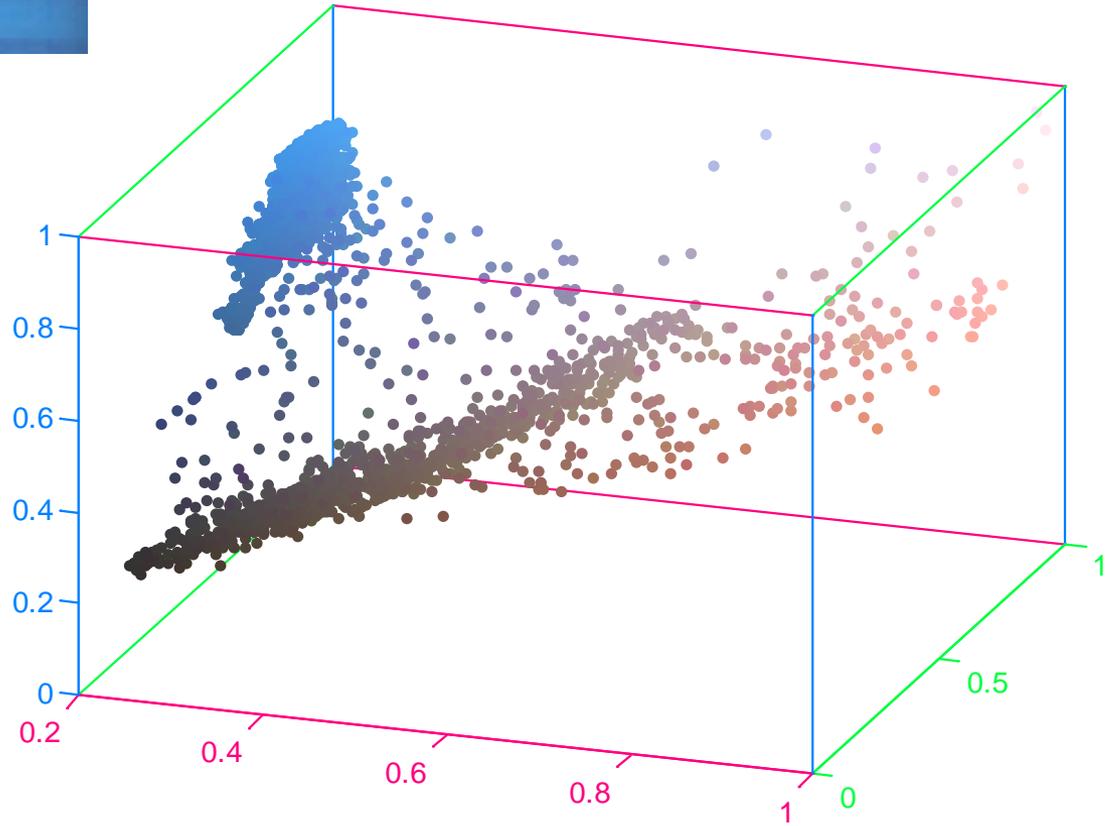
# Three papers and some updates

- › *A Bayesian Approach to Digital Matting*
  - › Yung-Yu Chuang, Brian Curless, David Salesin, and Richard Szeliski
  - › CVPR 2001
  
- › *Flash Matting*
  - › Jian Sun, Yin Li, Sing Bing Kang, and Harry Shum
  - › SIGGRAPH 2006
  
- › *A Closed Form Solution to Natural Image Matting*
  - › Levin, Lischinski, and Weiss
  - › CVPR 2006

# Chroma Keying







# Examples



<http://grail.cs.washington.edu/projects/digital-matting/image-matting/>



<http://www.fxguide.com/fxtips-242.html>

# Compositing Equation

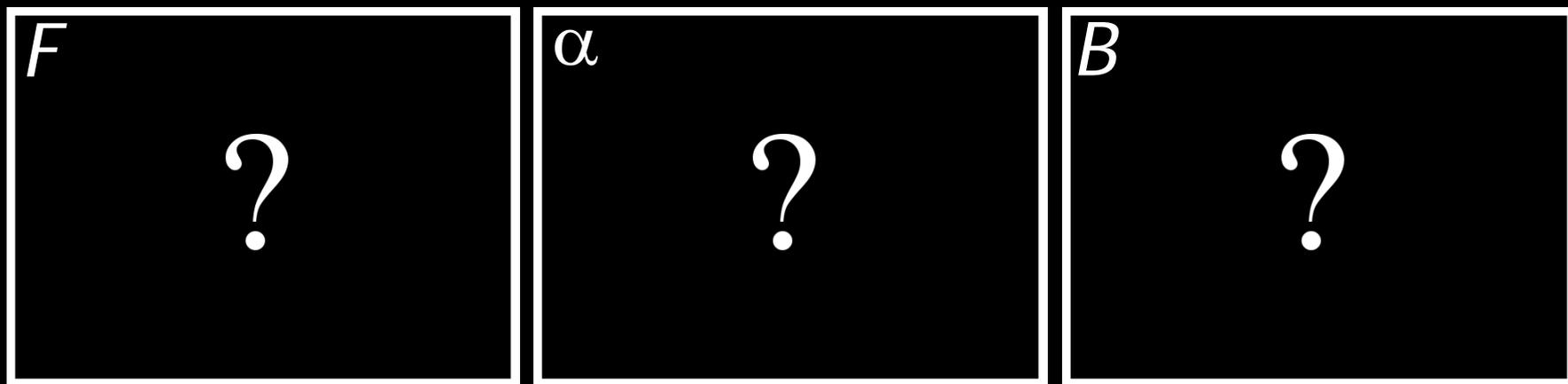
$$C = \alpha F + (1 - \alpha)B$$

composite                      foreground                      background

alpha channel

digital matting:

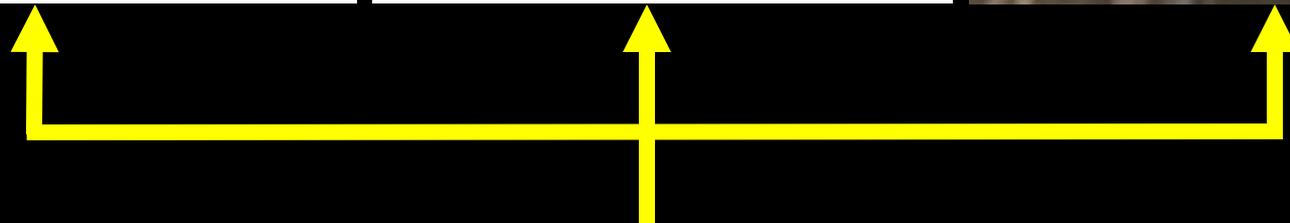
$\alpha$ ,  $F$ , and  $B$  are unknowns



$$C = \alpha F + (1 - \alpha)B$$

*Matting (reduce #unknowns)*

slides by Chuang et al.

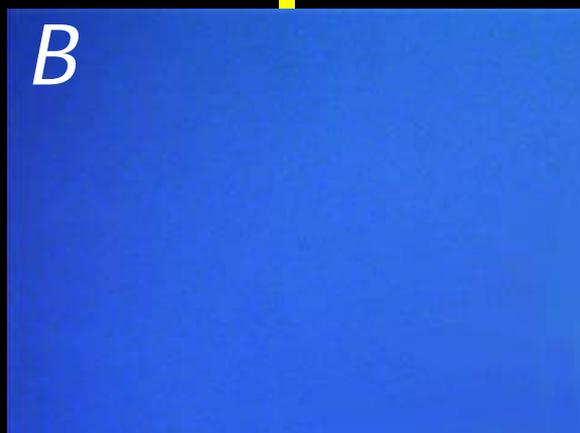


$$C = \alpha F + (1 - \alpha)B$$

*Matting (reduce #unknowns)*

slides by Chuang et al.





$$C = \alpha F + (1 - \alpha)B$$

blue screen  
matting

*Matting (reduce #unknowns)*

slides by Chuang et al.

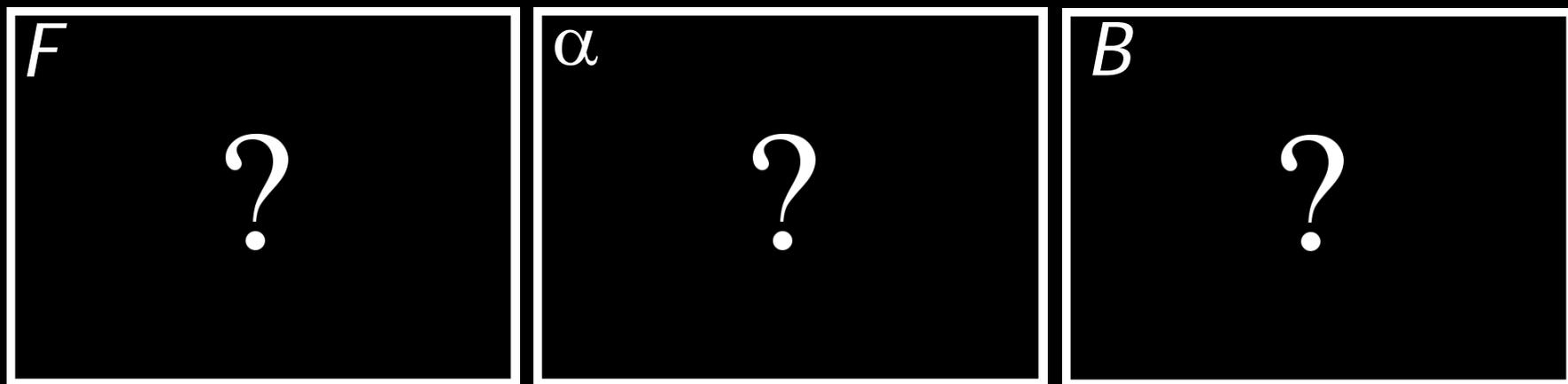


$$C = \alpha F + (1 - \alpha)B$$

$$C = \alpha F + (1 - \alpha)B$$

*Matting (add observations)*

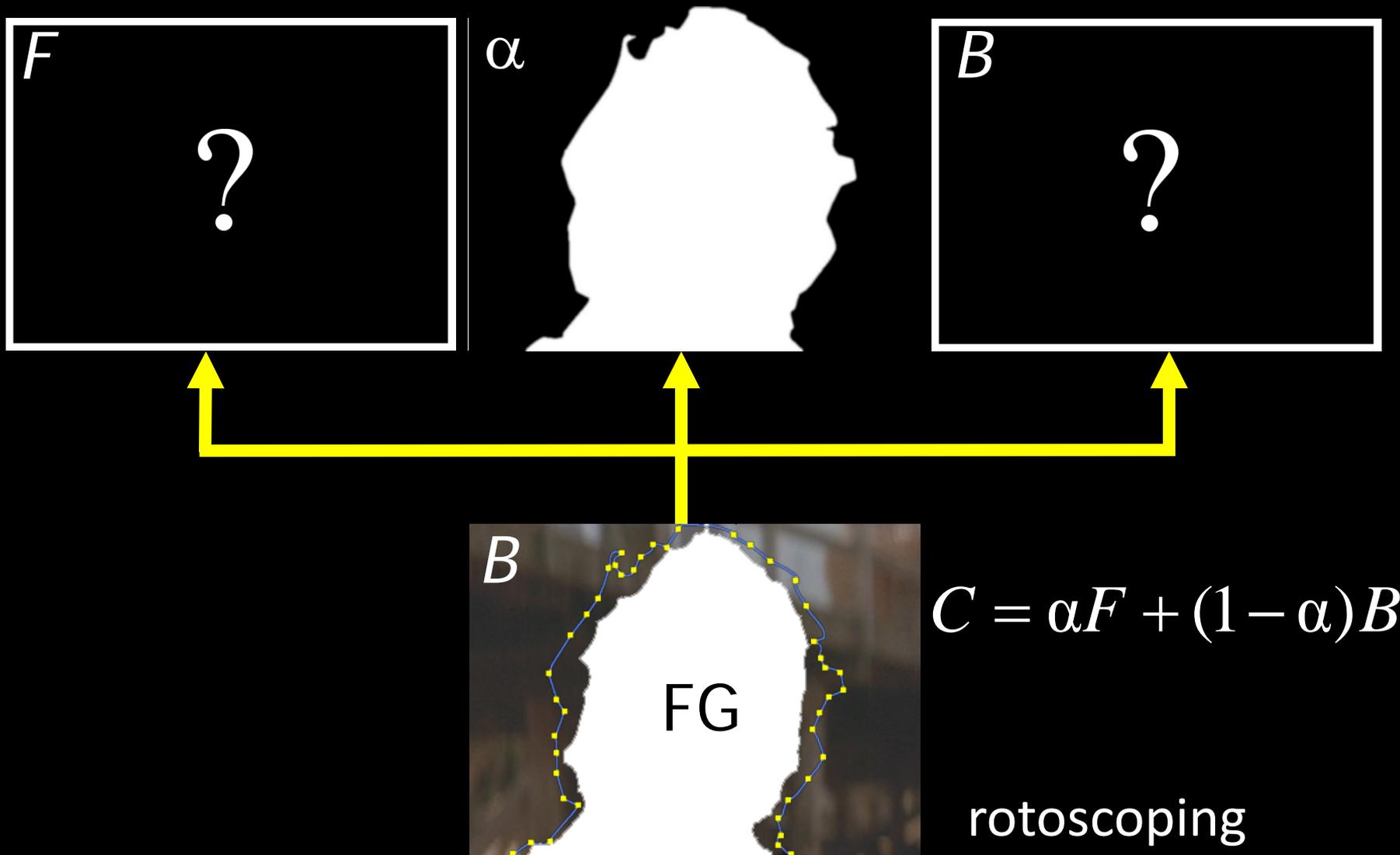
slides by Chuang et al.



$$C = \alpha F + (1 - \alpha)B$$

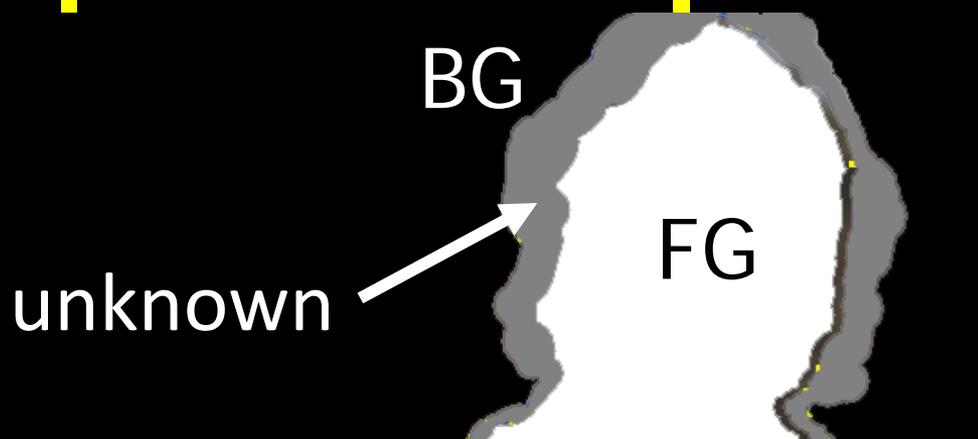
*Natural image matting*

slides by Chuang et al.



*Matting (add priors)*

slides by Chuang et al.



$$C = \alpha F + (1 - \alpha) B$$

Ruzon-Tomasi

*Matting (add priors)*

slides by Chuang et al.

# Another Way to Add Priors

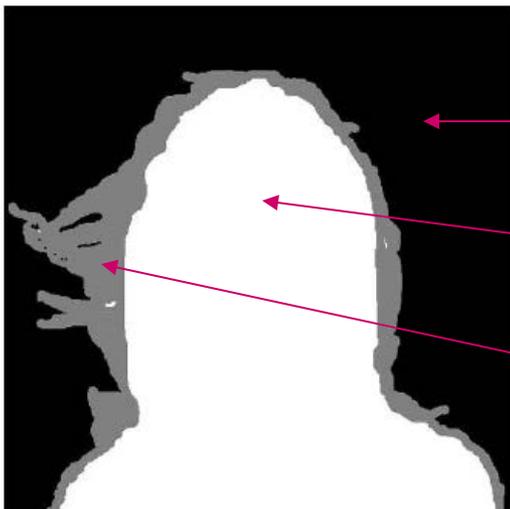
- › Draw scribbles



# User Segmentation



estimate  $\alpha$ ,  $F$ , and  $B$  for all pixels in the unknown region



definite background

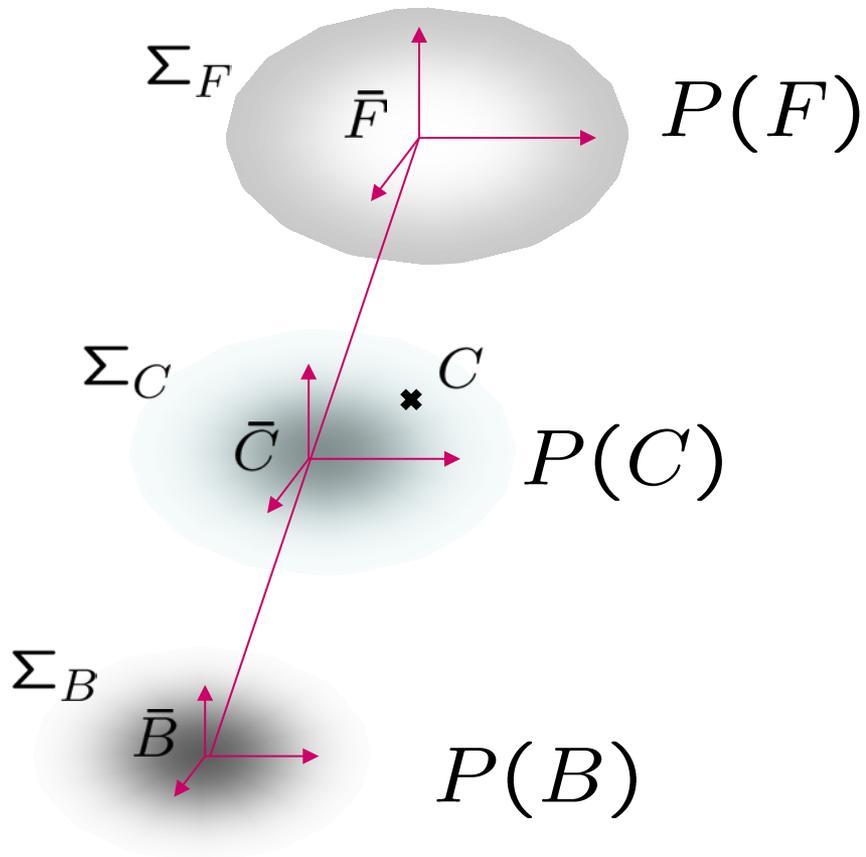
definite foreground

unknown region

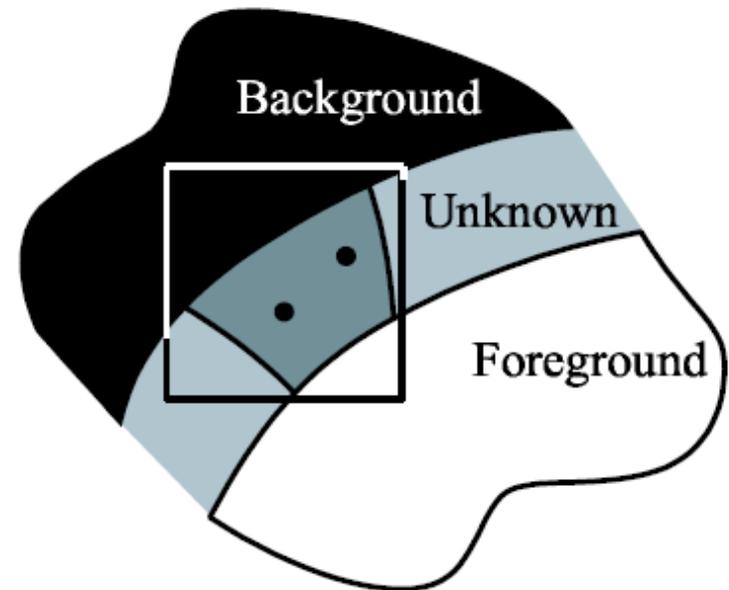
trimap

# A Probabilistic View

paired Gaussians

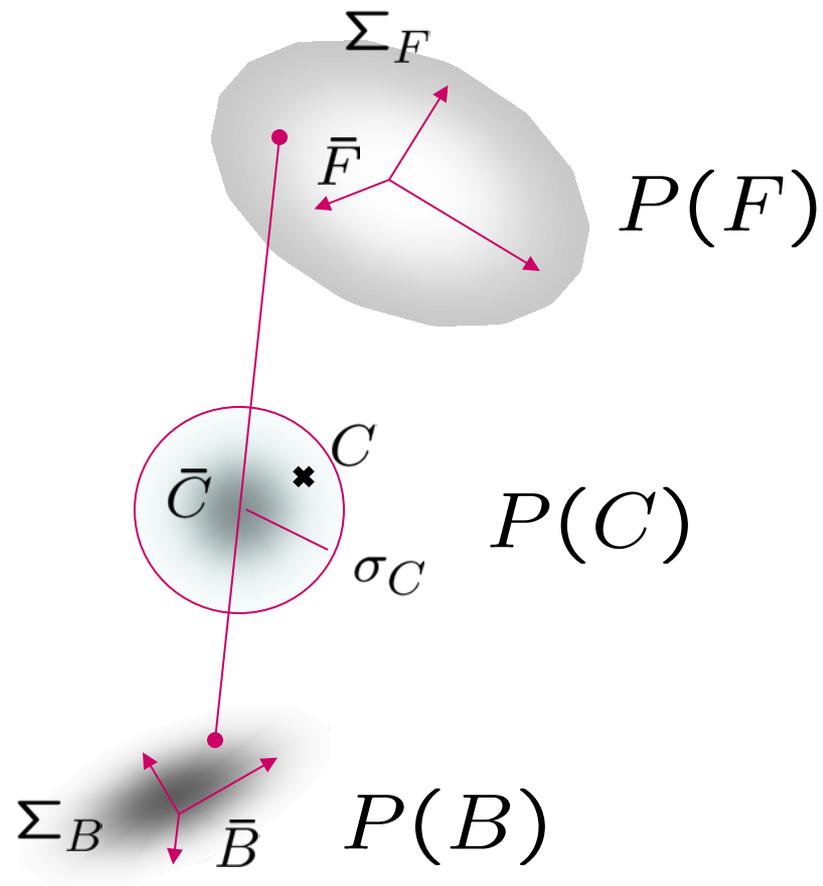


Ruzon-Tomasi

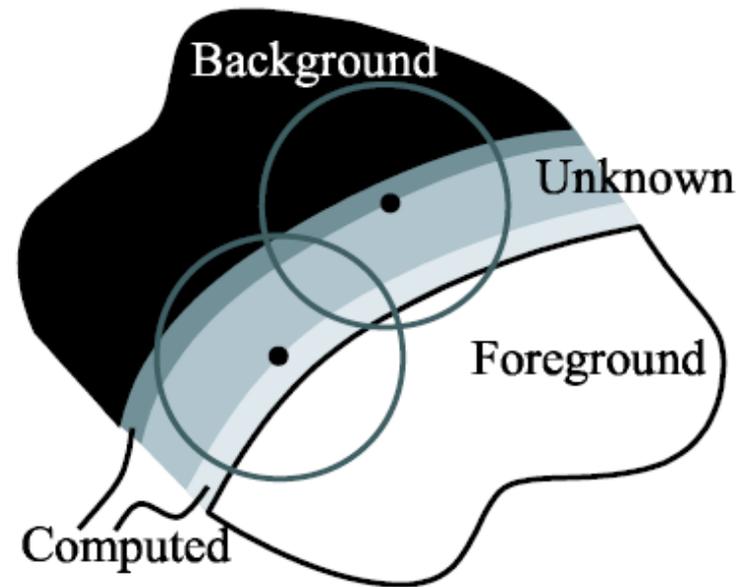


R, G, B colors

# Bayesian



# Bayesian





# Bayesian image matting

slides by Chuang *et al.*



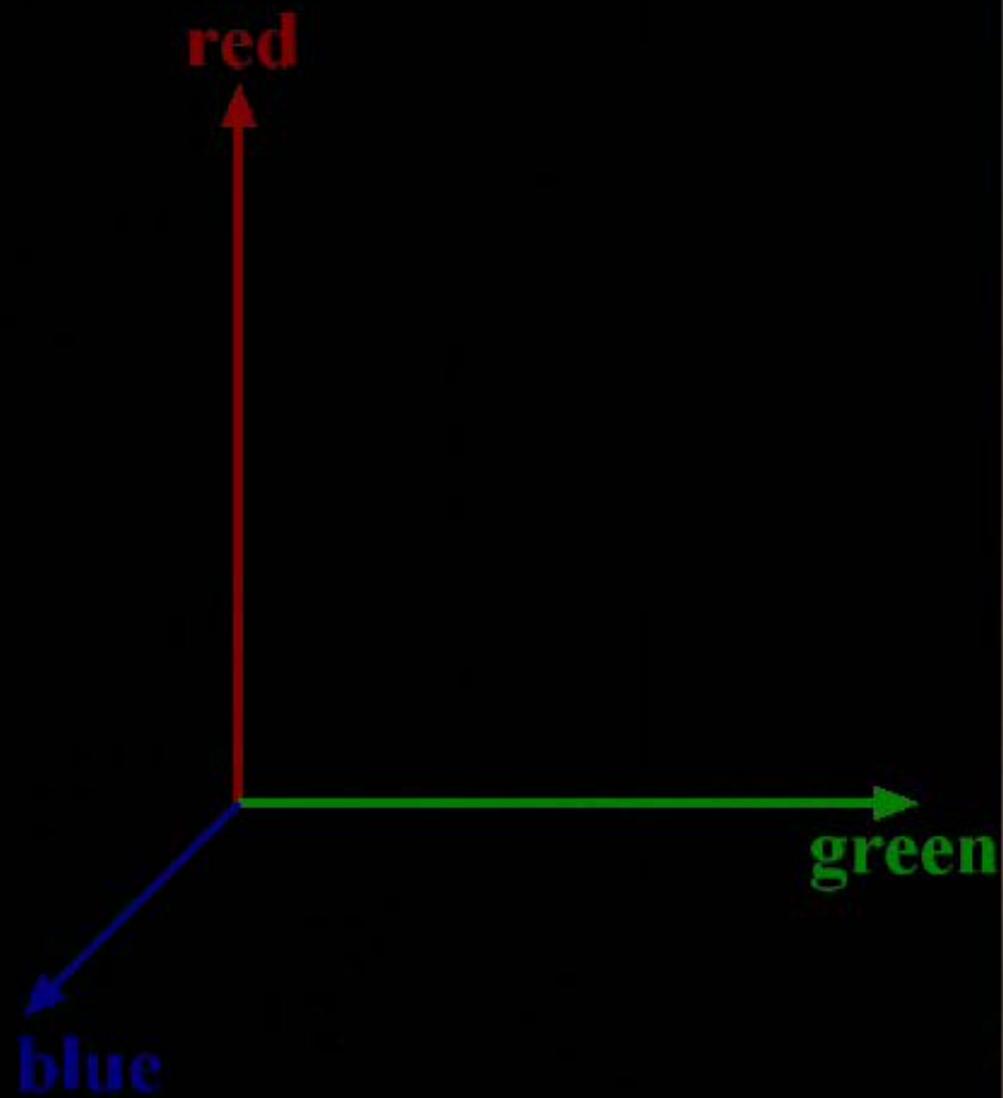
# Bayesian image matting

slides by Chuang *et al.*

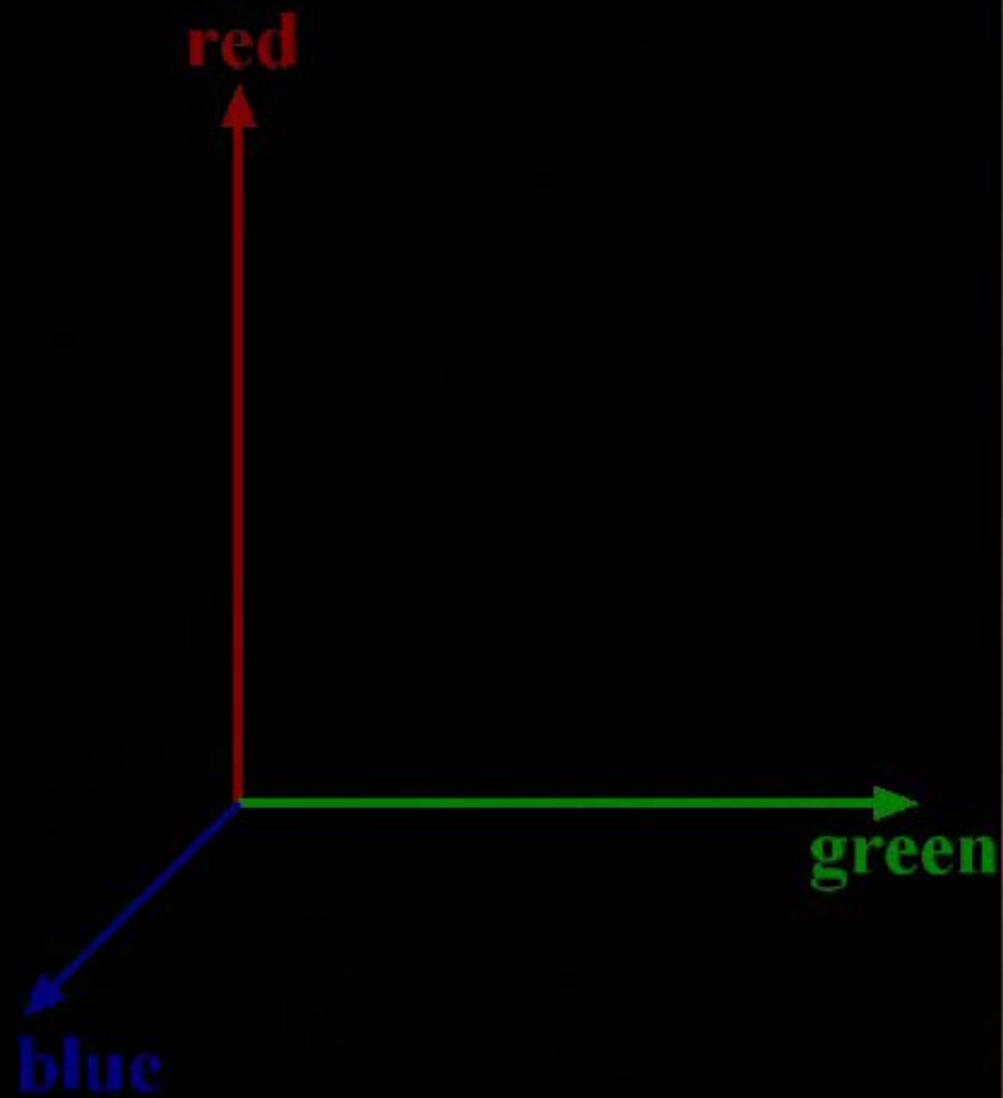


# Bayesian image matting

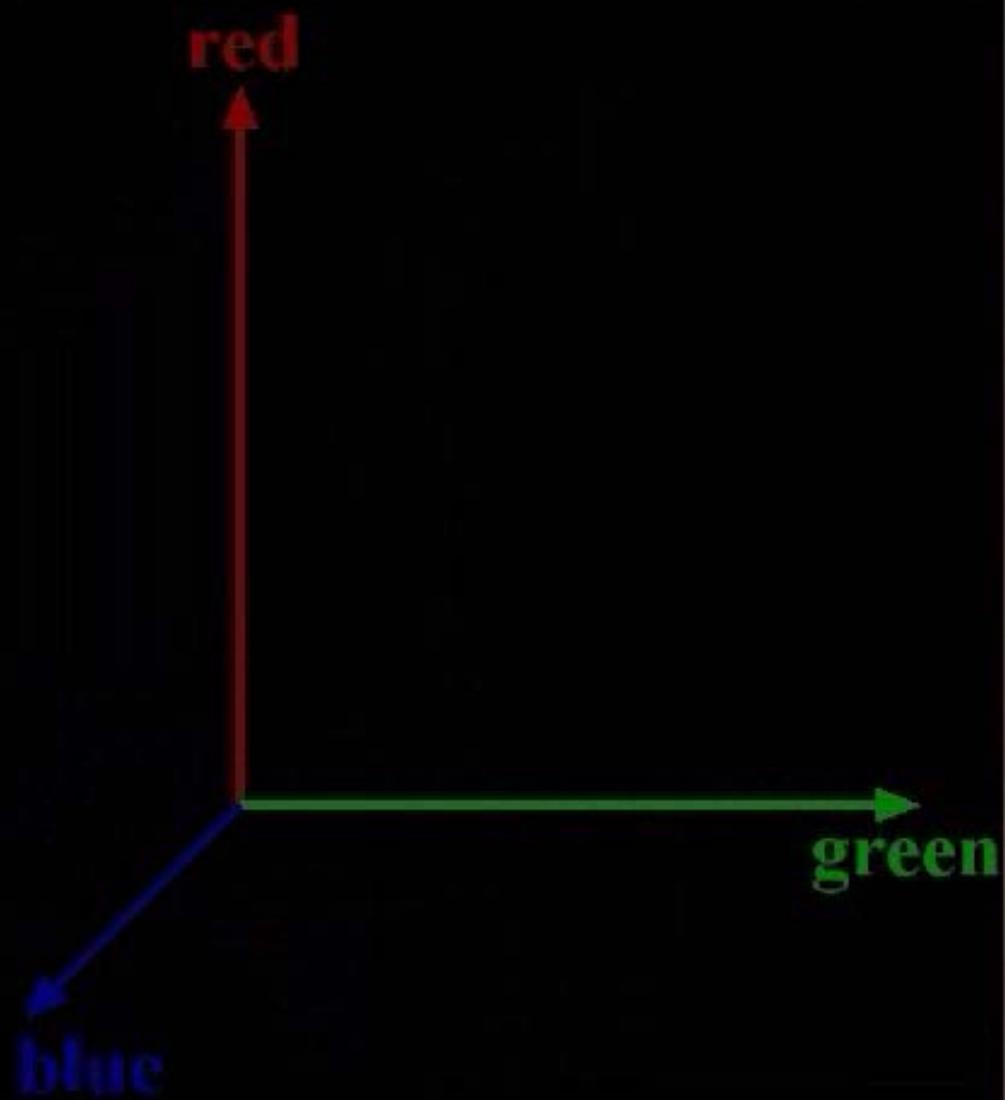
slides by Chuang *et al.*



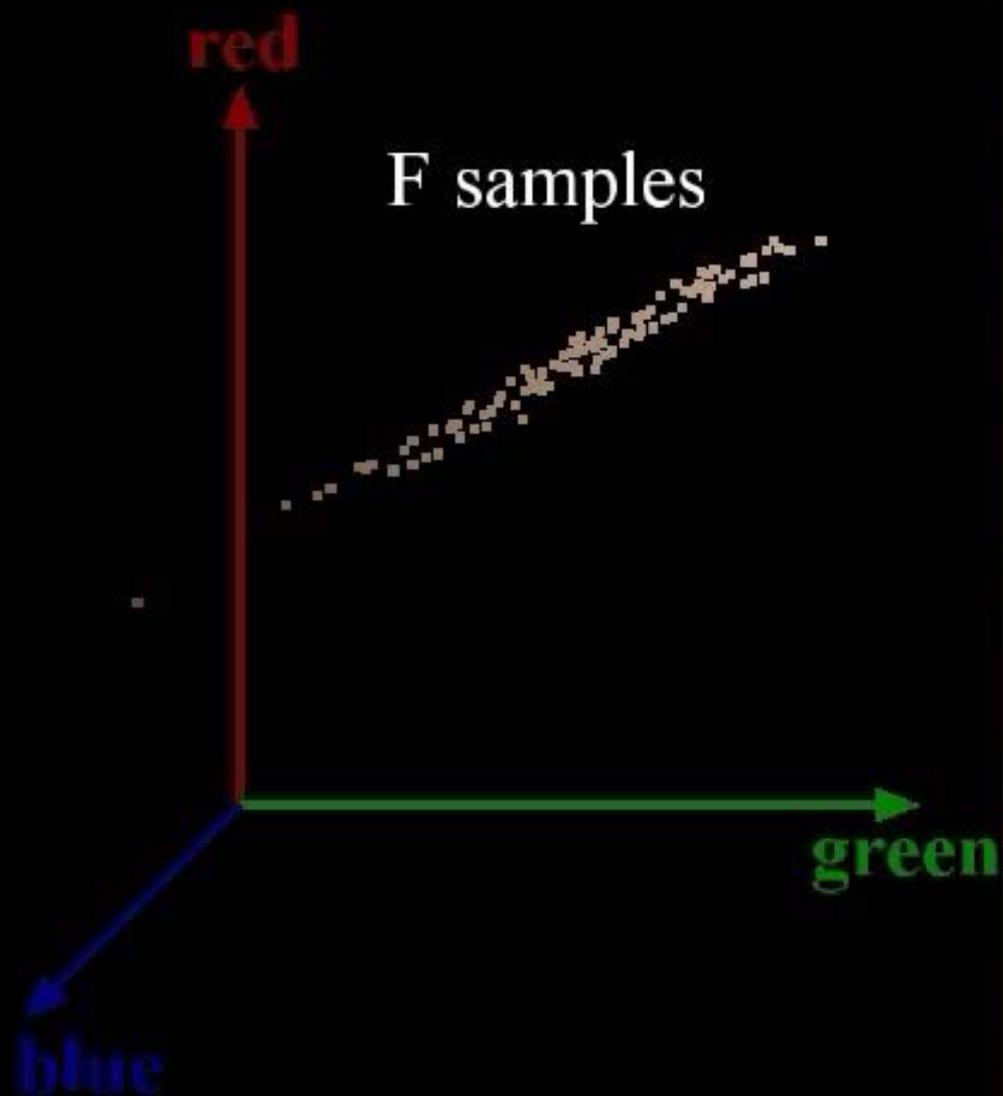
slides by Chuang *et al.*



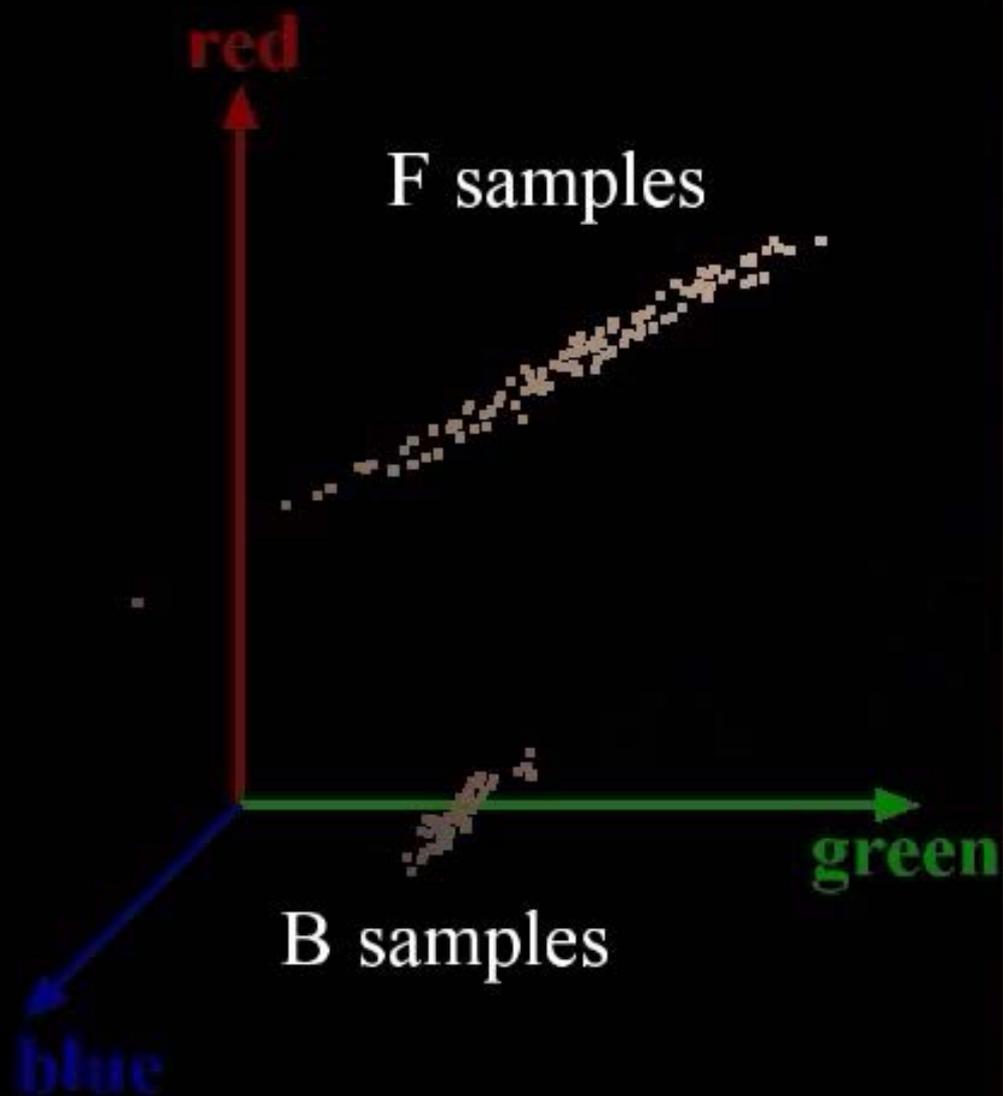
slides by Chuang *et al.*



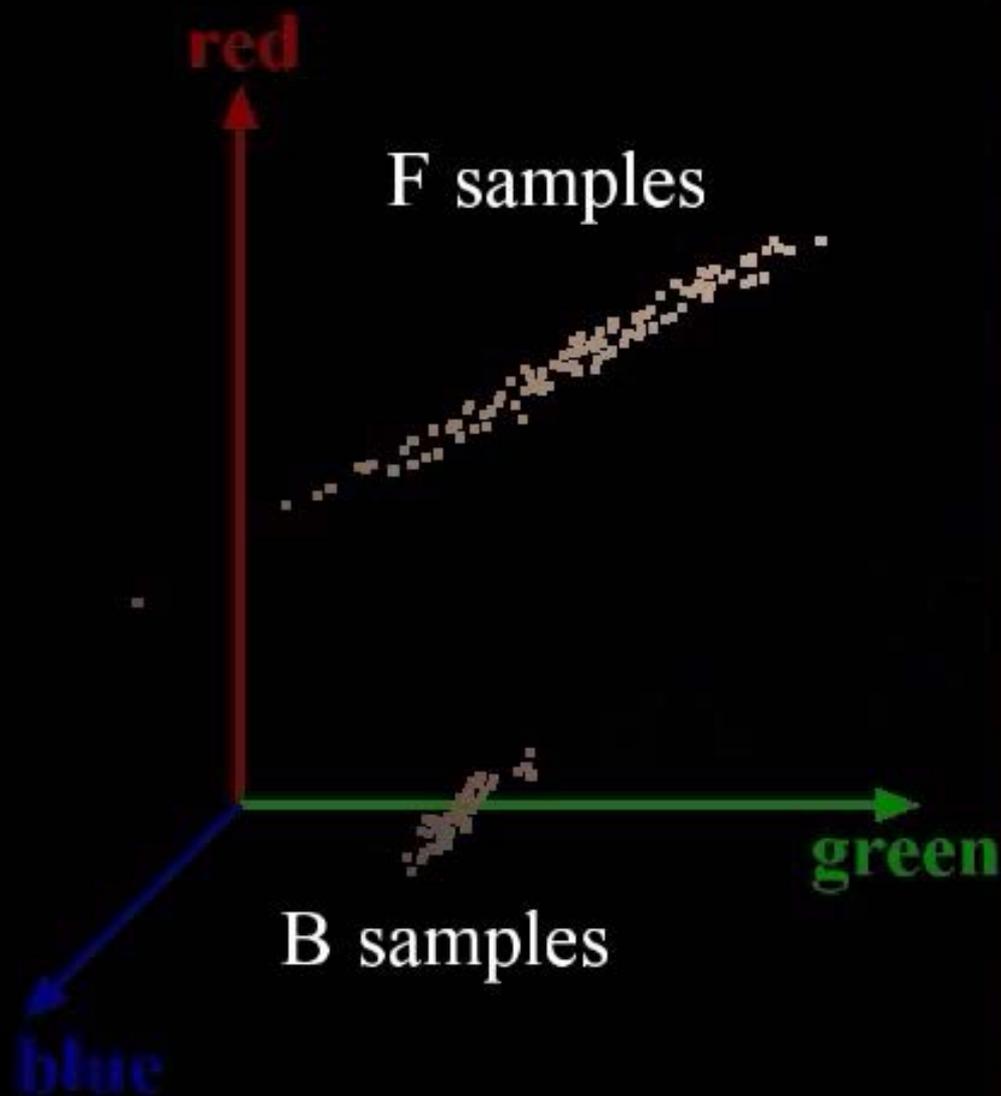
slides by Chuang *et al.*



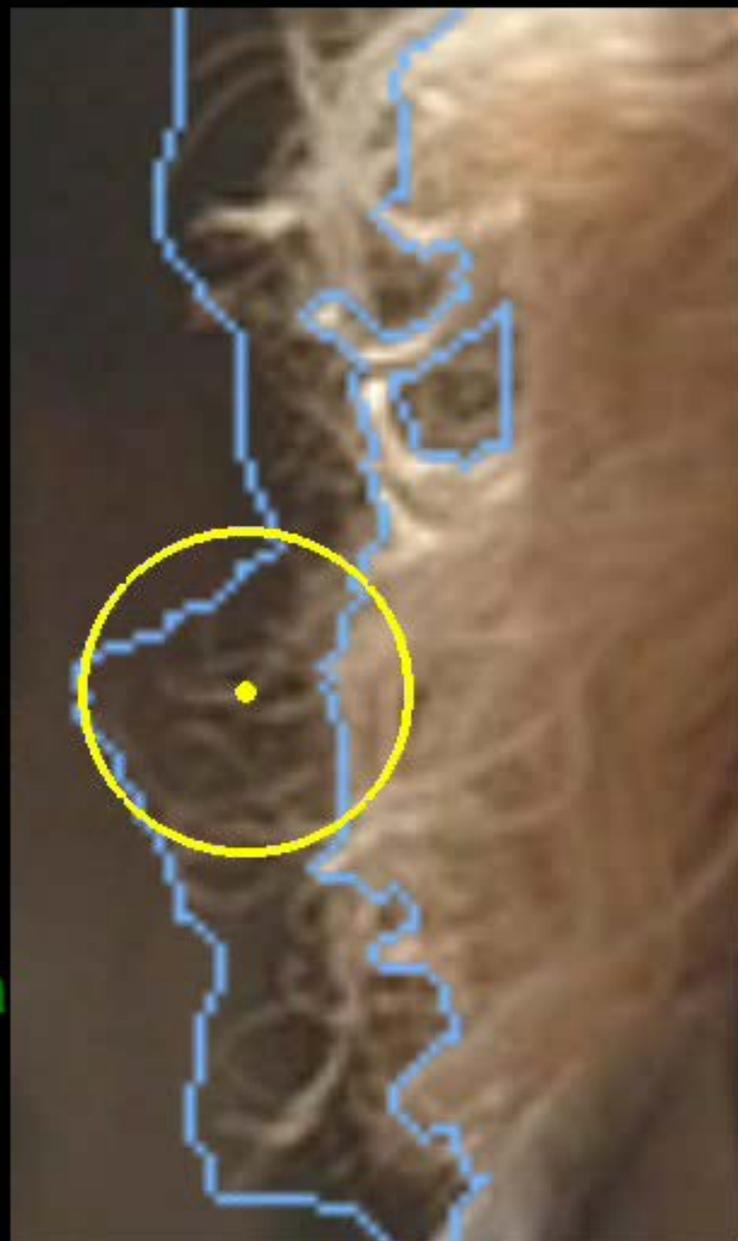
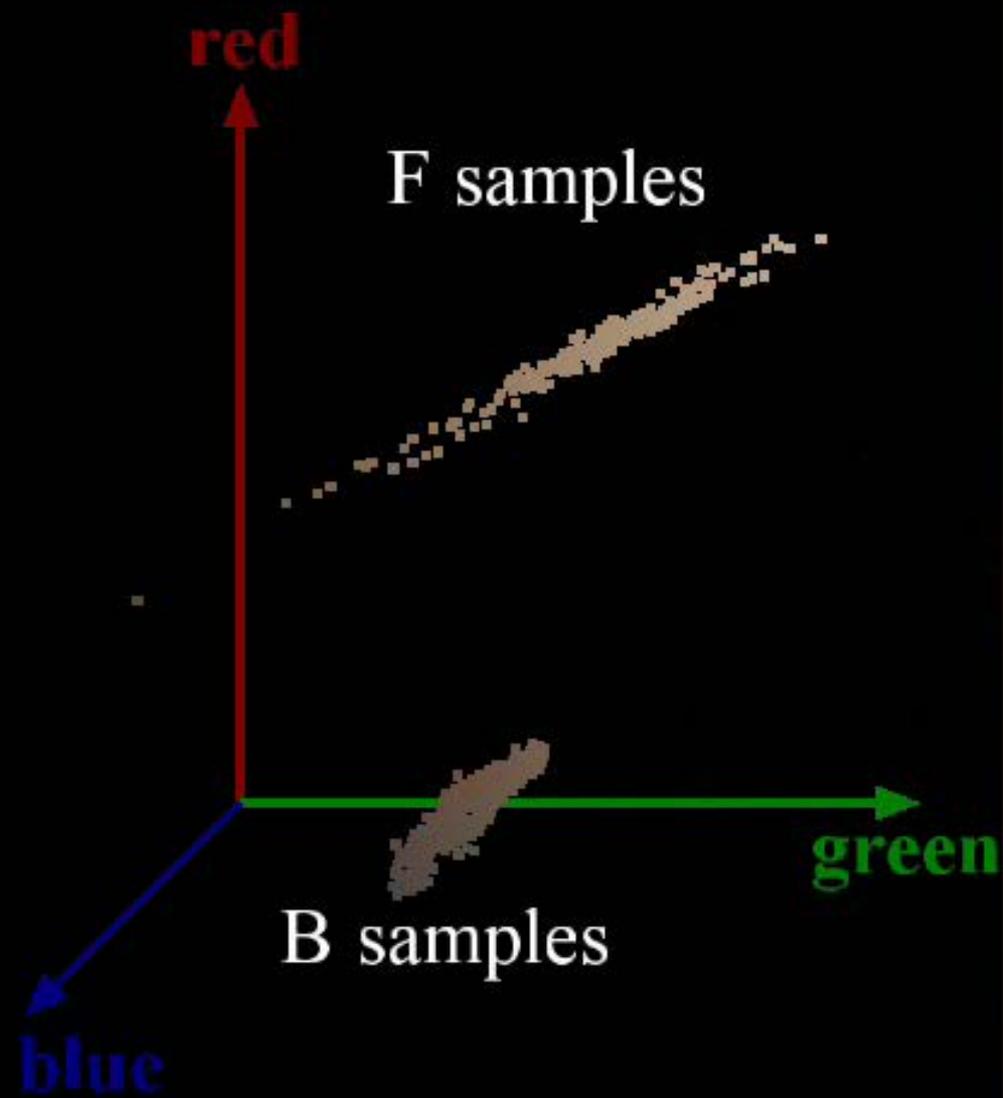
slides by Chuang *et al.*



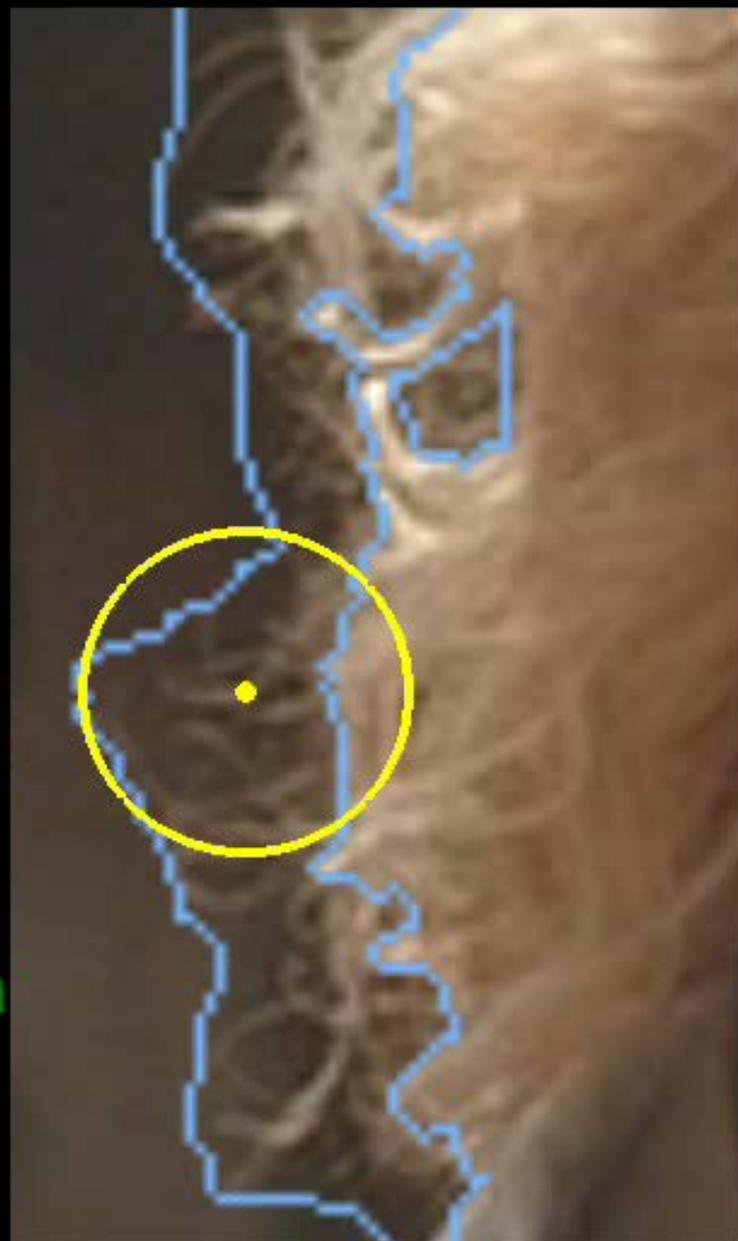
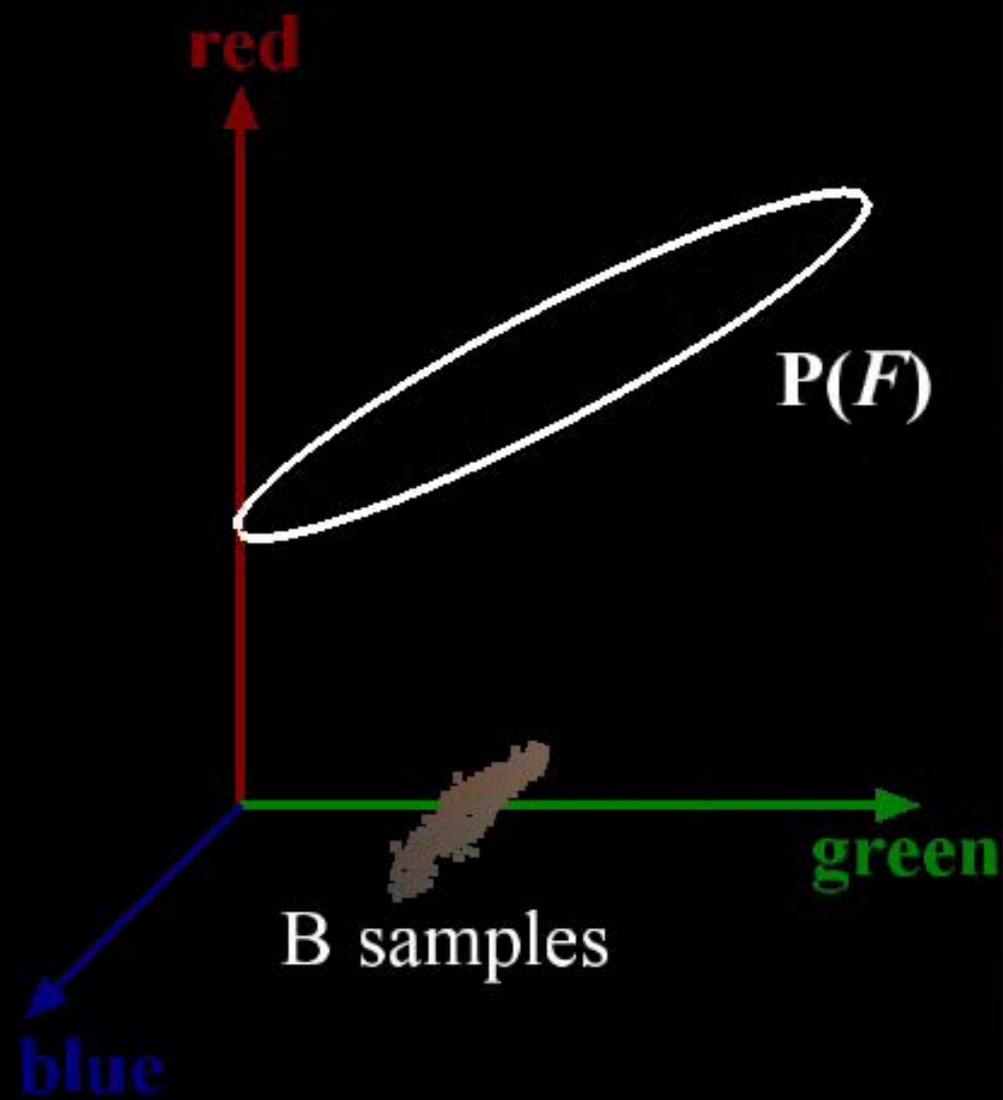
slides by Chuang *et al.*



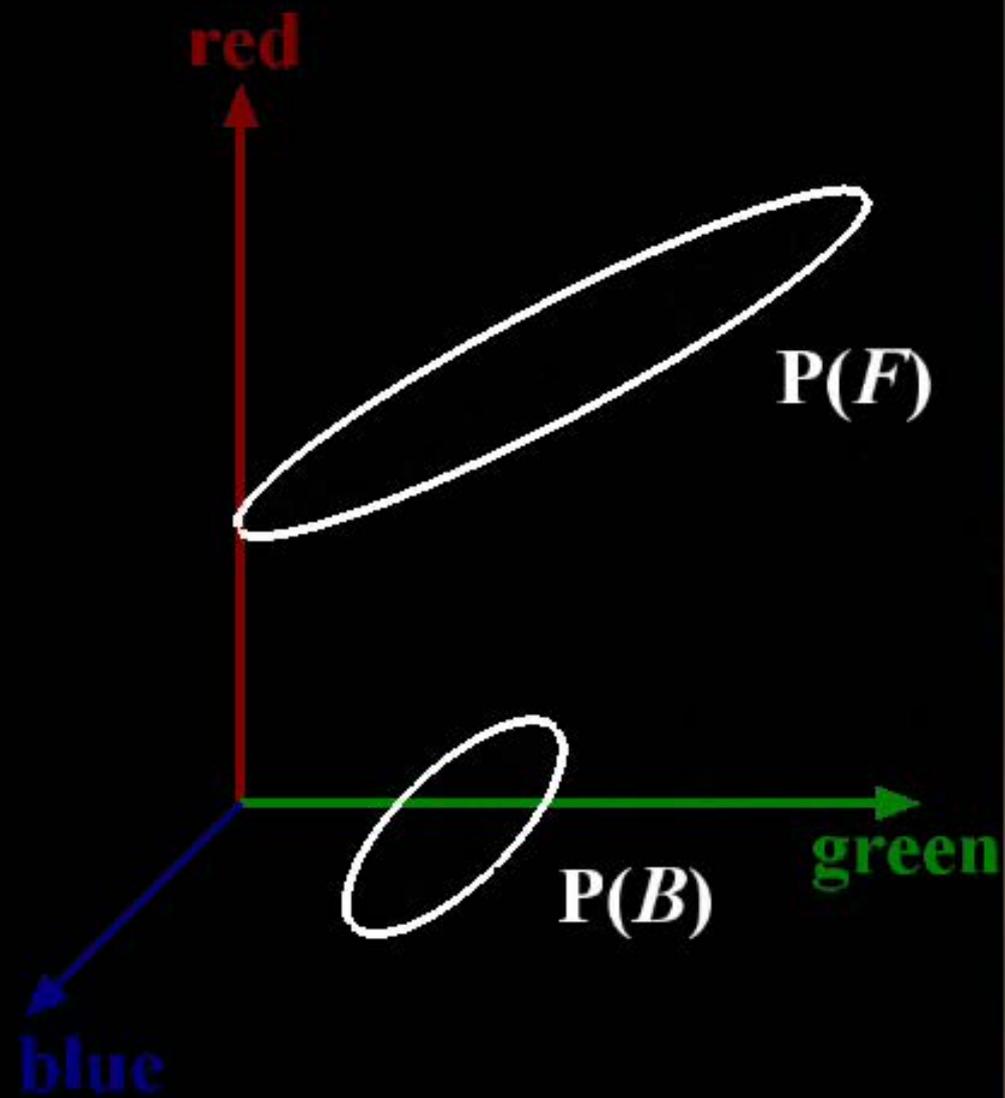
slides by Chuang *et al.*



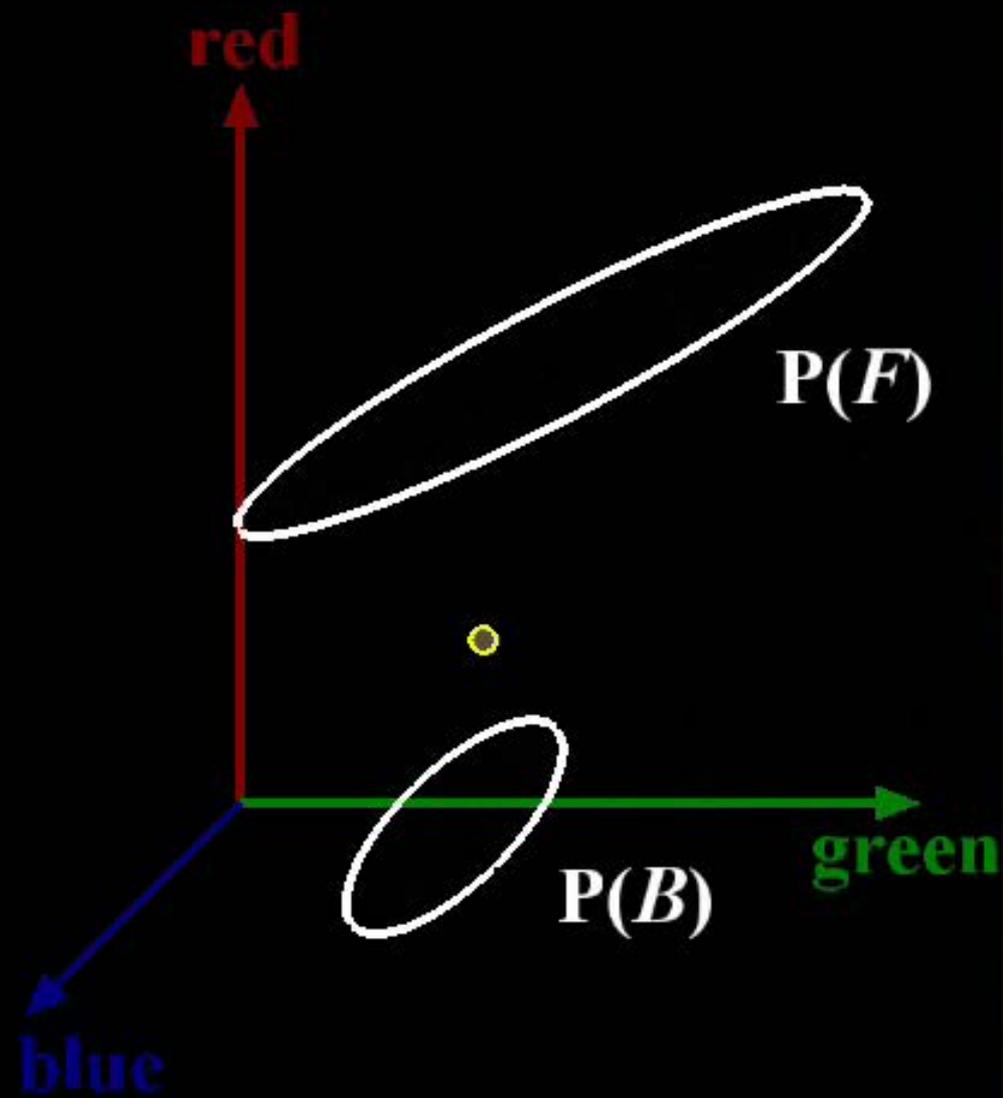
slides by Chuang *et al.*



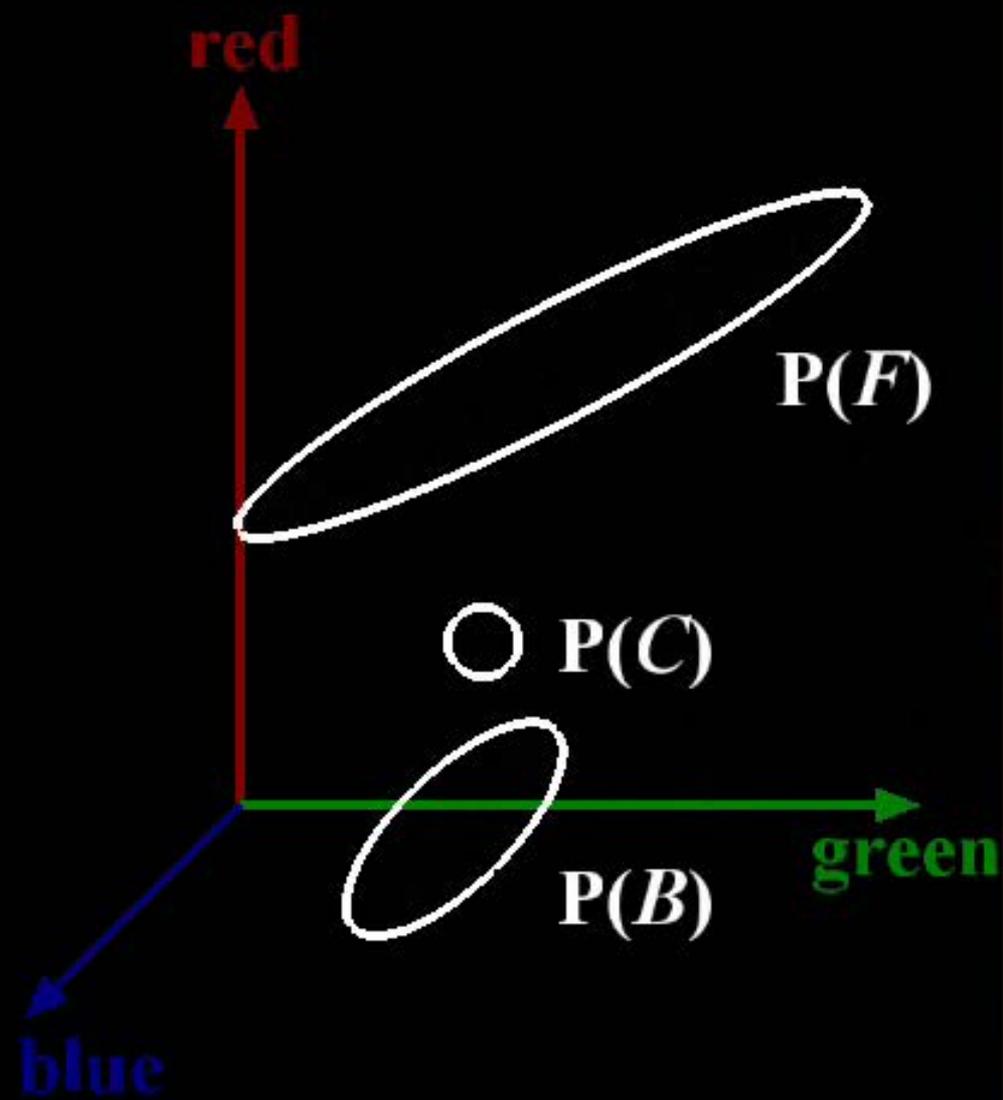
slides by Chuang *et al.*



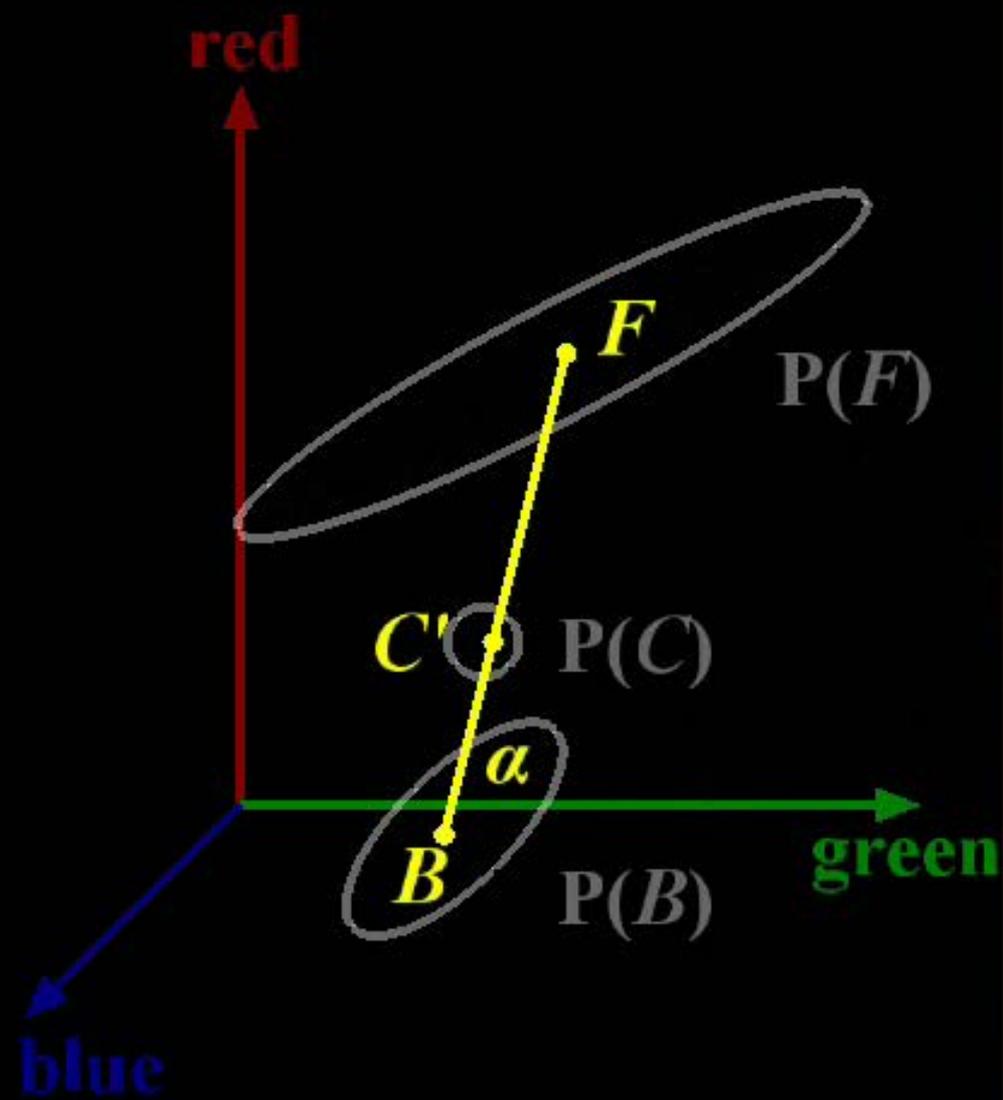
slides by Chuang *et al.*



slides by Chuang *et al.*



slides by Chuang *et al.*



slides by Chuang *et al.*

# Bayesian Framework

## › Maximum *a posteriori* (MAP)

$$\arg \max_{F, B, \alpha} P(F, B, \alpha | C)$$

$$= \arg \max_{F, B, \alpha} P(C | F, B, \alpha) P(F) P(B) P(\alpha) / \underline{\underline{P(C)}}$$

$$= \arg \max_{F, B, \alpha} \log P(C | F, B, \alpha) + \log P(F) + \log P(B) + \log P(\alpha)$$

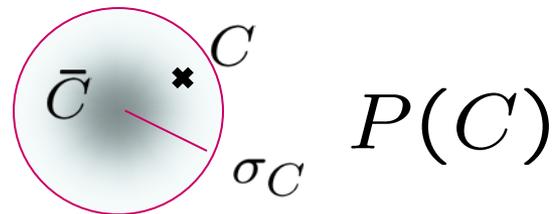
likelihood and priors

# Log Likelihood

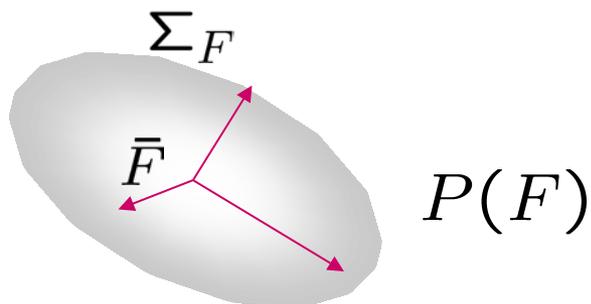
$$\bar{C} = \alpha F + (1 - \alpha)B$$

› Gaussian error

$$\log P(C|F, B, \alpha) = -\frac{1}{2\sigma_C^2} \|C - \alpha F - (1 - \alpha)B\|^2$$



# Priors



$$\log P(F) = -(F_i - \bar{F})^T \Sigma_F^{-1} (F_i - \bar{F}) / 2$$

contribution of a nearby pixel  $p_i$ :

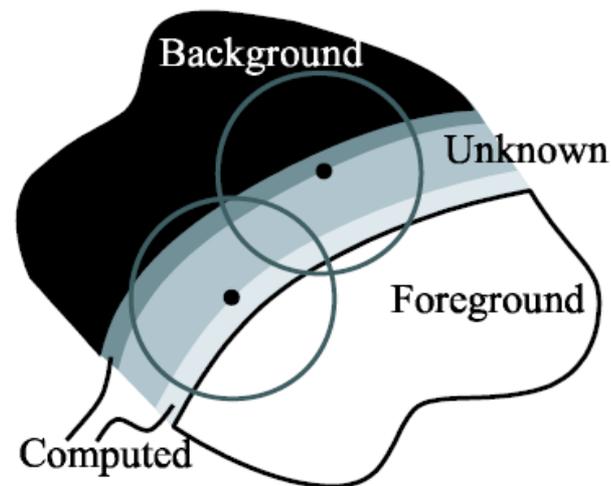
$$w_i = \alpha_i^2 g_i$$

$$\bar{F} = \frac{1}{W} \sum_{i \in \mathcal{N}} w_i F_i$$

$$\Sigma_F = \frac{1}{W} \sum_{i \in \mathcal{N}} w_i (F_i - \bar{F})(F_i - \bar{F})^T$$

$$W = \sum_{i \in \mathcal{N}} w_i$$

Bayesian



$P(B)?$   $P(\alpha)?$

# Optimization

- › Iteratively solve for  $F$  and  $B$  with fixed alpha, and then solve for alpha with fixed  $F$  and  $B$

$$\arg \max_{F, B, \alpha} P(F, B, \alpha | C)$$

$$= \arg \max_{F, B, \alpha} \log P(C | F, B, \alpha) + \log P(F) + \log P(B) + \log P(\alpha)$$

# Alternate Optimization Scheme

## Solve for $F$ and $B$

- › Taking the partial derivatives with respect to  $F$  and  $B$  and setting them equal to 0

$$\begin{bmatrix} \Sigma_{\bar{F}}^{-1} + I\alpha^2/\sigma_C^2 & I\alpha(1-\alpha)/\sigma_C^2 \\ I\alpha(1-\alpha)/\sigma_C^2 & \Sigma_{\bar{B}}^{-1} + I(1-\alpha)^2/\sigma_C^2 \end{bmatrix} \begin{bmatrix} F \\ B \end{bmatrix} \\ = \begin{bmatrix} \Sigma_{\bar{F}}^{-1}\bar{F} + C\alpha/\sigma_C^2 \\ \Sigma_{\bar{B}}^{-1}\bar{B} + C(1-\alpha)/\sigma_C^2 \end{bmatrix}$$

$$[6\text{-by-}6] [6\text{-by-}1] = [6\text{-by-}1]$$

## Solve for Alpha

- › Projecting the observed color  $C$  onto the line segment  $FB$  in color space

$$\alpha = \frac{(C - B) \cdot (F - B)}{\|F - B\|^2}$$

taking the partial derivatives with respect to alpha  
and setting it equal to 0

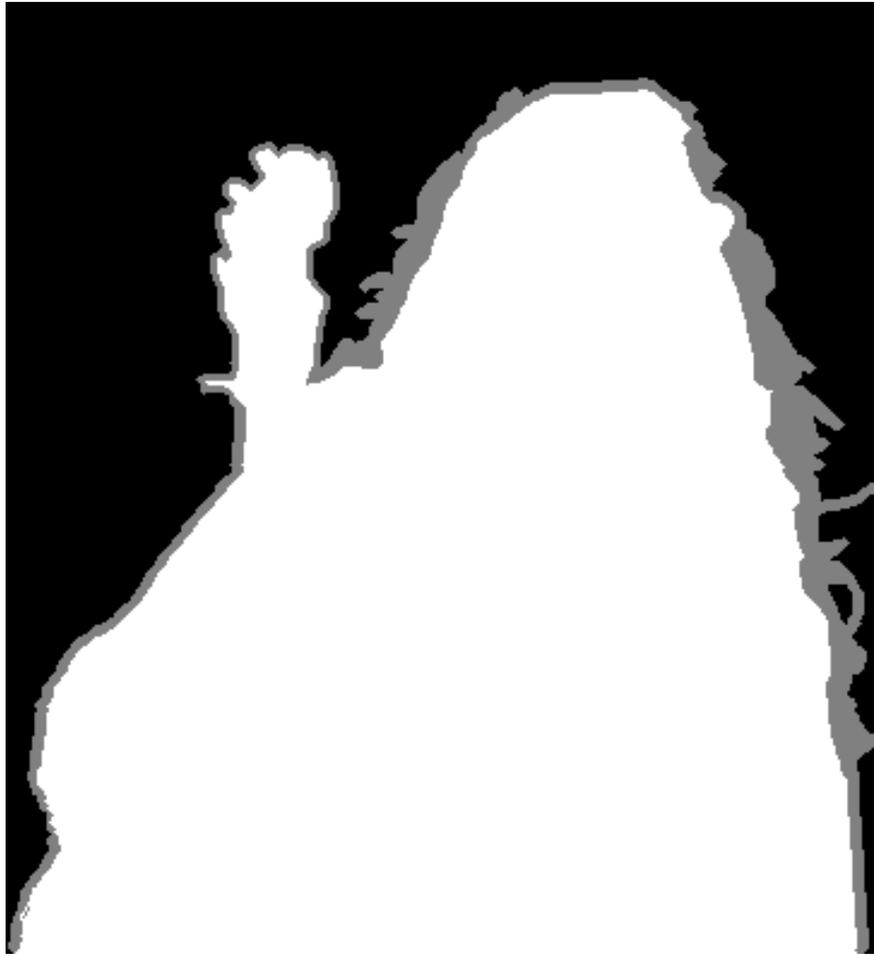
$$\arg \max_{F, B, \alpha} P(F, B, \alpha | C)$$

$$= \arg \max_{F, B, \alpha} \log P(C | F, B, \alpha) + \log P(F) + \log P(B) + \log P(\alpha)$$



trimap

alpha



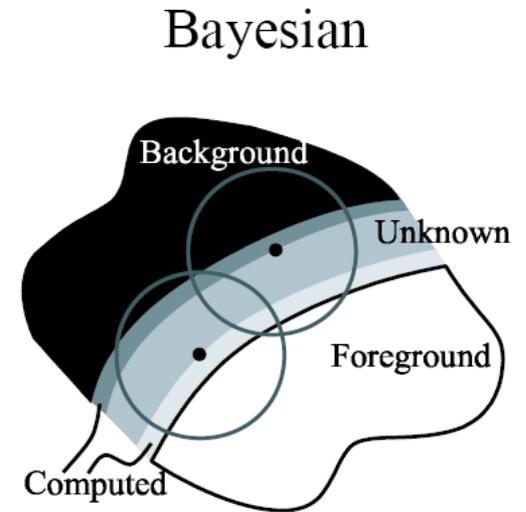
Results



## Results

# Questions

- › Color or grayscale?
- › Time complexity?
  - › Solving 6x6 linear equations
  - › Computing covariance matrices



# Flash Matting



$I^f$



$I$



$$\begin{aligned} I &= \alpha F + (1 - \alpha)B, \\ I^f &= \alpha F^f + (1 - \alpha)B^f \end{aligned}$$

# Flash Model

point light source radiance

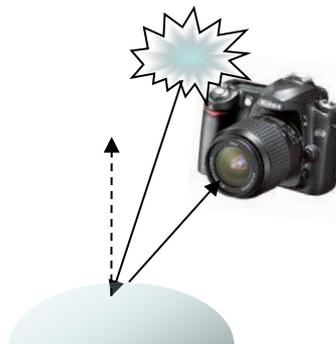
$$E = L \cdot \rho(\omega_i, \omega_o) \cdot r^{-2} \cdot \cos \theta$$

reflectivity

distance

angle between flash direction  
and surface normal

the flash intensity falls off quickly with distance  $r$



# Assumptions

- › Only the appearance of the foreground is dramatically changed by the flash
- › The input image pair is pixel aligned

$$B^f \approx B$$



$$I^f = \alpha F^f + (1 - \alpha)B$$

# Foreground Flash Matting

## › Subtracting

$$I = \alpha F + (1 - \alpha)B$$

$$I^f = \alpha F^f + (1 - \alpha)B$$



$$\underline{I'} = I^f - I = \alpha(F^f - F) = \alpha F'$$

the *flash-only* image



# Joint Bayesian Flash Matting

$$\begin{aligned} & \arg \max_{\alpha, F, B, F'} \log P(\alpha, F, B, F' | I, I') \\ &= \arg \max_{\alpha, F, B, F'} \log P(I | \alpha, F, B) + \log P(I' | \alpha, F') \\ & \quad + \log P(F) + \log P(B) + \log P(F') + \log P(\alpha) \end{aligned}$$

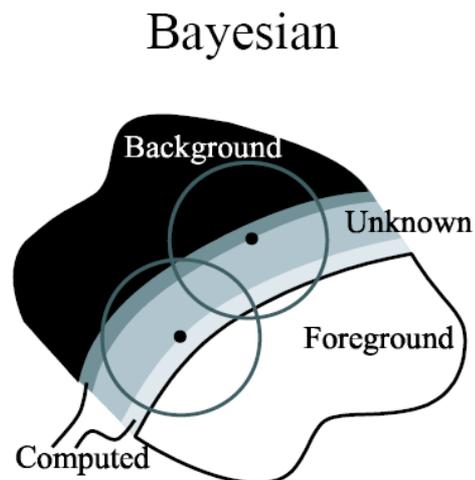
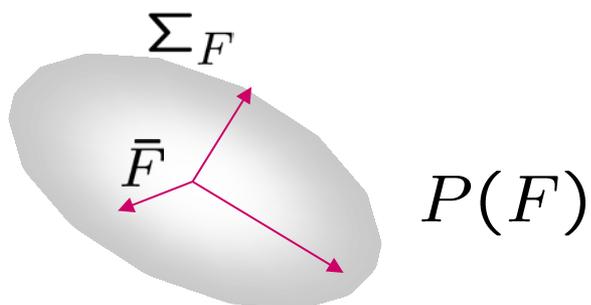
$$\log P(I | \alpha, F, B) = -\frac{1}{2\sigma_I^2} \|I - \alpha F - (1 - \alpha)B\|^2 \leftarrow ?$$

$$\log P(I' | \alpha, F') = -\frac{1}{2\sigma_{I'}^2} \|I' - \alpha F'\|^2$$

# Priors

$$\log P(F) = -(F_i - \bar{F})^T \Sigma_F^{-1} (F_i - \bar{F}) / 2$$

$$\log P(F') = -(F'_i - \bar{F}')^T \Sigma_{F'}^{-1} (F'_i - \bar{F}') / 2$$



# Optimization

› Iteratively and alternately

$$\begin{bmatrix} \Sigma_F^{-1} + \mathbf{I}\alpha^2/\sigma_I^2 & \mathbf{I}\alpha(1 - \alpha)\sigma_I^2 & \mathbf{0} \\ \mathbf{I}\alpha(1 - \alpha)\sigma_I^2 & \Sigma_B^{-1} + \mathbf{I}\alpha^2/\sigma_I^2 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \Sigma_{F'}^{-1} + \mathbf{I}\alpha^2/\sigma_{I'}^2 \end{bmatrix} \begin{bmatrix} F \\ B \\ F' \end{bmatrix}$$

$$= \begin{bmatrix} \Sigma_F^{-1}\bar{F} + I\alpha/\sigma_I^2 \\ \Sigma_B^{-1}\bar{B} + I(1 - \alpha)/\sigma_I^2 \\ \Sigma_{F'}^{-1}\bar{F}' + I'\alpha/\sigma_{I'}^2 \end{bmatrix}$$

$$\alpha = \frac{\sigma_{I'}^2 (F - B)^T (I - B) + \sigma_I^2 F'^T I'}{\sigma_{I'}^2 (F - B)^T (F - B) + \sigma_I^2 F'^T F'}$$

# "Joint" Bayesian

$$\alpha = \frac{\sigma_{I'}^2 (F - B)^T (I - B) + \sigma_I^2 F'^T I'}{\sigma_{I'}^2 (F - B)^T (F - B) + \sigma_I^2 F'^T F'}$$

$$F' \approx 0 \quad \Rightarrow \quad \alpha \approx (F - B)^T (I - B) / (F - B)^T (F - B)$$

[Chuang *et al.*]

$$F \approx B \quad \Rightarrow \quad \alpha \approx F'^T I' / F'^T F'$$

# Results

